Prediction of Survival for Older Hospitalized Patients: The HELP Survival Model

Joan M Teno, MD, MS, Frank E. Harrell, Jr.,† PhD, William Knaus, MD,† Russell S. Phillips, MD,‡ Albert W. Wu, MD, MPH¥ Alfred Connors, Jr., MD,† Neil S. Wenger, MD,§ Douglas Wagner, PhD,† Anthony Galanos, MD,¶ Norman A. Desbiens, MD,‖ and Joanne Lynn, MD, MA, MS#*

OBJECTIVE: To develop and validate a model estimating the survival time of hospitalized persons aged 80 years and older.

DESIGN: A prospective cohort study with mortality follow-up using the National Death Index.

SETTING: Four teaching hospitals in the US.

PARTICIPANTS: Hospitalized patients enrolled between January 1993 and November 1994 in the Hospitalized Elderly Longitudinal Project (HELP). Patients were excluded if their length of hospital stay was 48 hours or less or if admitted electively for planned surgery.

MEASUREMENTS: A log-normal model of survival time up to 711 days was developed with the following variables: patient demographics, disease category, nursing home residence, severity of physiologic imbalance, chart documentation of weight loss, current quality of life, exercise capacity, and functional status. We assessed whether model accuracy could be improved by including symptoms of depression or history of recent fall, serum albumin, physician's subjective estimate of prognosis, and physician and patient preferences for general approach to care.

RESULTS: A total of 1266 patients were enrolled over a 10-month period, (median age 84.9, 61% female, 68% with one or more dependency), and 505 (40%) died during an average follow-up of more than 2 years. Important prognostic factors included the Acute Physiology Score of APACHE III collected on the third hospital day, modified Glasgow coma score, major diagnosis (ICU categories together, congestive heart failure, cancer, orthopedic, and all other), age, activities of daily living, exercise capacity, chart documentation of weight loss, and global quality of life. The Somers' Dxy for a model including these factors was 0.48 (equivalent to a receiver-operator curve (ROC) area of 0.74, suggesting good discrimination). Bootstrap estimation indicated good model validation (corrected Dxy of 0.46, ROC of 0.73). A nomogram based on this log-normal model is presented to facilitate calculation of median survival time and 10th and 90th percentile of survival time.

A count of geriatric syndromes or comorbidities did not add explanatory power to the model, nor did the hospital of patient recruitment, depression, or the patient preferences for general approach to care. The physician's perception of the patient's preferences and the physician's subjective estimate of the patient's prognosis improved the estimate of survival time significantly.

CONCLUSIONS: Accurate estimation of length of life for older hospitalized persons may be calculated using a limited amount of clinical information available from the medical chart plus a brief interview with the patient or surrogate. The accuracy of this model can be improved by including measures of the physician's perception of the patient's preferences for care and the physician's subjective estimate of prognosis.
J Am Geriatr Soc 48:S16–S24, 2000.

Key words: prognosis; severity of illness; survival analysis; statistical models; older people

During the past 3 decades, prognostic models have been developed for use as case mix adjusters, for risk adjustment and quality assurance, and as decisional aids for seriously ill patients.[1–6] With the exception of the SUPPORT prognostic model, these models apply only to those hospitalized in an intensive care unit or estimate only short-term mortality. The SUPPORT prognostic model examined hospitalized seriously ill patients with one of nine high mortality illnesses. Rather than analyze hospital survival or short-term mortality, the SUPPORT prognostic model evaluated survival time up to 180 days. Several studies developed prognostic models of survival specifically for older persons.[7–9] These studies are limited either by the small number of variables they tested or their limited generalizability.

Our previous research[10,11] and that of others[12,13] suggests that healthcare providers weight age as an important factor in decisions about the use of life-sustaining treatment

From the Center for Gerontology and Health Care Research, Brown University, Providence, Rhode Island; †University of Virginia School of Medicine, Charlottesville, Virginia; ‡Beth Israel Deaconess Medical Center and Harvard Medical School, Boston, Massachusetts; ¥School of Hygiene and Public Health, Johns Hopkins University School of Medicine, Baltimore, Maryland; §UCLA Medical Center, Los Angeles, California; ¶Duke University Medical Center, Durham, North Carolina; University of Tennessee College of Medicine – Chattanooga Unit, Chattanooga, Tennessee; and the ‖Center to Improve Care of the Dying, George Washington University, Washington, DC.

Address correspondence to Joan M Teno, MD, MS, Center for Gerontology and Health Care Research, Box GB 219, 171 Meeting Street, Rm 222, Brown University, Providence, RI 02912.

0002-8614/00/$3.50

and the level of resource utilization for older persons. These findings are difficult to reconcile with research showing that age explains only a small portion of the likelihood that a patient will die.[14] Physicians may be overly pessimistic about the survival probability of older patients. Improved estimates of survival may encourage decision-making based on physiologic rather than chronologic age and reduce age-related differences in treatment decisions. Prognostic models may have even more important practical applications for older persons themselves. Either for viatical policies (i.e., conversion of person's life insurance at a reduced rate depending on the patients' longevity, with the buyer cashing the life insurance policy in when the person dies)[15,16] or for planning for their needs in old age, older persons may find it helpful to have prognostic information that calculates median survival time accurately.

In this report, we examine whether an accurate prognostic model can be developed using the minimal amount of clinically relevant data collected at the time of hospital admission for those aged 80 years and older. Additionally, we examine the degree to which the model's accuracy may be improved by the addition of variables that would require a more extensive interview with a patient or surrogate. In this latter exploratory analysis, we examine the association of depression, patient preferences for aggressiveness of treatment, physician's report of patient's preferences, and physician prognostic estimates with patient longevity.

METHODS

Study Population

Subjects were participants in HELP, the Hospitalized Elderly Longitudinal Project, a multicenter study of outcomes and decision-making for hospitalized adults aged 80 years or older

HELP enrolled patients admitted to the hospital who were aged 80 or older. Patients were excluded if they did not speak English or were foreign nationals admitted for a specific medical procedure; had AIDS or multiple trauma; were admitted for hospice care, to psychiatry, or for elective surgery; were admitted to a hospital ward after transfer from another hospital; died or were discharged within 72 hours of hospitalization; or were scheduled for discharge within 48 hours of admission.

Enrollment took place between January 1993 and November 1994 at Beth Israel Hospital, Boston, MA; MetroHealth Medical Center, Cleveland, OH; Marshfield Clinic/St. Joseph's Hospital, Marshfield, WI; and the University of California, Los Angeles Medical Center, Los Angeles, CA. Institutions with a larger volume of older admissions were randomly sampled so that an approximately equal number of persons were enrolled at each site. All patients had complete follow-up to 1 year by monthly phone calls, and we performed National Death Index matches, which allowed us a total maximum follow-up of 711 days.

Data Collection

Data was collected data by prospective review of the medical record and an interview with the patient and the surrogate (defined as the person who would make decisions if the patient was unable to do so). All variables considered for the prognostic model were prespecified, with the primary goal assessing the accuracy of a model that relied on a limited amount of clinical information from the medical record and an interview with the patient or surrogate. We used data obtained from a surrogate only if the patient was unable to be interviewed. Our secondary goal was to assess whether the accuracy of the model could be improved by including additional information from a lengthier patient (or surrogate) interview.

We gathered data from the medical record regarding reasons for admission, patient age, sex, other medical conditions, and acute physiologic and neurologic status as measured by the Acute Physiology Score of APACHE III,[1] measured on the third day after study entry. We used an adaptation of the 14 geriatric conditions created by Winograd and colleagues[17] to abstract information relating to hearing impairment, vision impairment, confusion or disorientation, and history of depression, being bedridden or on prolonged bed rest, hip fracture or replacement, appetite change, social problems, documentation of frailty or becoming frail, urinary incontinence, fecal incontinence, a fall at home within the last 3 months, and unintended weight loss.

The chart abstractor wrote verbatim the stated reason for admission, usually based on the physician orders or the initial admission history and physical exam. These reasons were classified into broad diagnostic categories (e.g., orthopedic, cardiovascular, respiratory, geriatric syndromes, neurological, or cancer) by one of the authors (AG). For those patients who enrolled with a disease severity and conditions qualifying them for SUPPORT, we used their SUPPORT disease category. Based on apparent differences in survival by disease, we collapsed the broad categories into the five following categories: (1) congestive heart failure; (2) cancer diagnoses, (3) orthopedic diagnoses, (4) qualifying for SUPPORT with acute respiratory failure, multiple organ system failure, or nontraumatic coma; and (5) all other diagnoses. The SUPPORT diagnoses of acute respiratory failure and multiple organ system failure required that patients be hospitalized in an intensive care unit. For coma, SUPPORT required a Glasgow Coma Score of 9 or greater and survival for at least 48 hours in the hospital.

Interviews with the patient and surrogate were conducted in the first week of hospitalization (median 3 days; 25th to 75th percentile range of 3 to 5). Both patient and surrogate reported on patient activities of daily living (ADL) performance 2 weeks before hospital admission, the patient's physiological reserve as measured by a revised version of the Duke Activity Status Index,[18] and self-rated quality of life. ADLs were assessed using a modified version of the Katz Activities of Daily Living,[19] with questions indicating dependence on assistance for the following basic functions: eating, continence, toileting, transferring, bathing, dressing, and walking. The index was scored on a 0 to 7 scale, with a higher score indicating more dependencies. The Duke Activity Status Index is a patient-reported measure of ability to perform a number of personal, household, and recreational activities, each of which is associated with known metabolic costs, in order to assess cardiovascular capacity. For this study, the item on sexual function was deleted, and three items about yard work, moderate recreation, and strenuous recreation were combined into a single item.[20] The Duke Activity Status Index was scored so that a higher score indicated greater metabolic capacity. Quality of life was assessed using a 5-point scale ranging from poor to excellent, with a higher score indicating better quality of life.

To assess whether the accuracy of the model could be improved by including additional variables, we examined measures of depression (the Profile of Mood State subscale[21]), perceived social support,[22] history of recent falls, body mass index, and poor vision. Perceived social support was defined by a series of questions that ask the respondent to state the likelihood (choosing from "not-at-all" to "very likely") that there would be someone to provide help with transportation, help with personal care, or other assistance. These variables were specified a *priori* and based on a review of the literature.

We also examined the association between survival time and patient and physician preferences for general approach to care. Assessment of whether the patient desired an approach to care that focused on extending life or on patient comfort was assessed with the following interview question:

If you had to make a choice at this time, would you prefer a course of treatment that focuses on extending life as much as possible, even if it means having more pain and discomfort, or would you want a plan of care that focuses on relieving pain and discomfort as much as possible, even if that means not living as long?

Surrogate and physicians answered a similarly worded question. In addition, we examined whether the physicians' prognostic estimate for survival predicted survival. For prognosis, physicians were asked to rate the probability that the patient would still be alive 2 months following study and enrollment. The physician interview questions were asked between days 2 and 6, following study enrollment.

Handling of Missing Data

Interview data were not available for every patient, and, therefore, to avoid discarding too much information and resultant biases, we developed a substitution and imputation strategy for missing values of independent variables. We gave priority to patient rather than surrogate responses about functioning and quality of life. When the patient response was missing, we substituted a calibrated surrogate response. Based on the subset of cases for which both patient and surrogate responses were present, surrogate responses were calibrated to achieve a similar distribution to that of patient scores.[20] When neither patient nor surrogate response was available, an imputation strategy was used. Ordinal logistic regression models containing age, SUPPORT Physiology Score at Day 3, diagnosis, number of additional diagnoses, cancer diagnosis, site, interview status, and length of time in hospital before study entry were used to predict surrogate-reported Activities of Daily Living, quality of life, and Duke Activity Status Index. Surrogate responses were estimated instead of patient responses because surrogate responses were available for a broader range of situations. The estimated surrogate responses were then calibrated to the patient distribution in the same way that actual surrogate responses were calibrated, and then substituted for the patient response.

Analysis

Development of Predictive Model

Selection of potential predictor variables was based on review of the literature and clinical experience. All variables were specified a *priori*. We had three specific analytic goals. First, we aimed to examine the accuracy (as measured by discrimination and calibration) of a model that relied on information from the medical record and a brief interview with the patient or surrogate. This interview would include information from the patient or surrogate about the patients' perceived quality of life and functioning. Second, we conducted exploratory analyses to examine whether the predictive accuracy of this model would be improved by the inclusion of additional interview information. We tested whether measures of depression, social support, body mass index, difficulty with vision, and history of fall in the last 3 months predicted survival. Finally, we examined whether the inclusion of patient and physician preferences for approach to care affected long-term survival time.

We determined the optimal survival model by examining which model best fit the survival distribution. First we assessed whether the Cox[24] proportional hazard model was an adequate fit to the data and found that the proportional hazards assumptions were not met, because the importance of physiologic variables waned with time. We assessed the fit of the log-logistic, log-normal, and accelerated failure time parametric survival models by examining (1) the parallelism and linearity of the logit or probit transformed Kaplan-Meier survival estimates stratified by important prognostic factors plotted against log of follow-up of time and (2) the Kaplan-Meier distribution of the residuals from the model to check for logistic or normal distribution. We found that the log-normal model had the best fit and employed this survival model in our remaining analyses.

This model facilitated prediction of median survival time, which is the anti-log of the weighted linear combination of the independent variables. To depict the variability of individual survival times, we present the quartiles of the log-normal distribution. For example, the 10th and the 90th percentiles of the distribution specify an 80% prediction interval for an individual patient's survival time. That is, the median survival time may be 6 months, with 10th and 90th percentile being 3 and 18 months. The model's best estimate may be that the patient will survive 6 months. However, 80% of the patients with characteristics similar to those of this patient would die between 3 and 18 months.

We constructed three models. The first model predicts survival time with the inclusion of chart-based information, ADL, DASI, and self-rated quality of life. The second model included further information that would necessitate a longer interview with the patient. The third model examined the potential influence of patient and physician preferences on survival time. In constructing each of these models, we allowed continuous variables (age, coma score, APS, albumin, ADL, and DASI) to have nonlinear relationships with survival time by incorporating restricted cubic spline functions (i.e., piece-wise cubic polynomials).[23]

Evaluation of the Model

The accuracy of the model was assessed with measures of discrimination and calibration. Predictive discrimination (i.e., the ability of predictive model to separate those who die early from those who die late) was assessed using the Somers' Dxy rank correlation coefficient. This measure quantifies the association between predicted and observed survival time. Somers' Dxy is the probability of concordance minus the probability of discordance between predicted outcomes and observed outcomes for all possible pairs of patients with different predicted probabilities of whom the ordering of survival time could be inferred. A model with perfect ability to separate high and low risk patients would have a Somers' Dxy of 1.0. Calibration is a second measure of the model's accuracy. A calibration curve plots the relationship between the predicted survival time and actual survival time. Finally, we validated the final model using the bootstrap method, which estimates a correction for overfitting or "optimism" in the model fit to derive estimates of predictive accuracy that would be obtained in a new sample of similar patients.[25] With this method, the model is reestimated in 150 random samples from the original population and tested against the original sample. All computations were done using S-PLUS 4.5 (MathSoft, Inc., Seattle, WA) on the UNIX and Microsoft Windows systems using the Design library of S-PLUS biostatistical modeling functions.[26]

RESULTS

Study Population

During the enrollment period, 1266 patients (median age 84.8, 63% female) were enrolled in HELP. (Table 1) Most of the patients had one or more ADL dependencies. In the year following the index hospital admission, 505 patients died, with the majority of the deaths occurring after the patient was discharged from the enrollment hospitalization. Figure 1 depicts the survival experience to the maximum follow-up of 711 days. As shown in Figure 1, those older persons enrolled in a SUPPORT category of acute respiratory failure, multiorgan system failure or nontraumatic coma had a shorter survival time than those with congestive heart failure, an orthopedic condition, or other diagnoses.

Prognostic Model: Development and Validation

The association of independent variables included in the chart with limited interview variables (functional status and perceived quality of life) are shown in Figure 2, which shows the adjusted survival time ratio (the ratio of median predicted survival times after adjustment for other factors in the model) with 95% confidence intervals. A survival time ratio less than 1.0 indicates a reduced survival time (or increased risk of death). Those persons with functional impairment, as indicated by lower DASI scores or a higher number of ADL impairments, had a shortened survival time. Those with greater disease severity, as measured by APACHE III, had a reduced survival time. Persons who lost weight had nearly one-half the median survival time of those who had not lost weight. Both the count of the number of geriatric conditions or the site of recruitment were not independent predictors of survival and were dropped from subsequent analyses.

The univariate association of disease categories with survival persisted after adjustment; those with an orthopedic diagnosis lived twice as long as persons in other chronic disease categories. Age was associated with survival time. However, age did not have the same explanatory power as the person's disease severity, diagnosis, functional status, and modified Glasgow coma score, as shown in Figure 3 and as

Table 1. Description of the Study Population (n = 1266)

Demographics	
Sex (% female)	63%
Median age (25th, 75th percentile)	84.9 (82.3, 88.6)
Functional status and quality of life	
Median Activities of daily living (25th, 75th percentile)	1.05 (.484, 2.8)
Median Duke Activity Status Index (25th, 75th percentile)	
Quality of life	
Excellent	6% (72)
Very Good	8% (100)
Good	27% (341)
Fair/poor	59% (753)
Clinical data	
Disease class	
ARF/MOSF/Coma	4% (46)
CHF	9% (118)
Cancer	25% (321)
Orthopedic	9% (118)
All others	52% (663)
Median Acute Physiology Score (25th, 75th percentile) excluding coma score	22 (16, 30)
Glasgow Coma Score	
<10	2% (27)
10	0% (2)
11	1% (15)
12	2% (22)
13	2% (26)
14	26% (324)
15	67% (849)
Median albumin (25th, 75th percentile)	3.5/3.5/3.5
Unintended weight loss*	49% (507)

* Weight loss, data were available for 1028 patients.

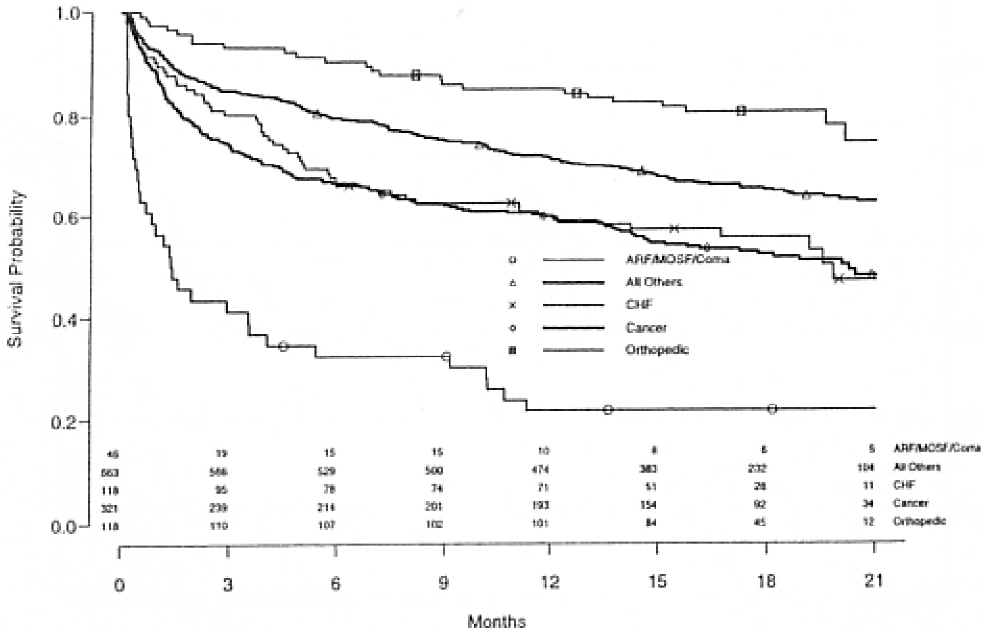

Figure 1. Survival Curve: Depicted is the Kaplan-Meier curve of the major disease categories. As shown, those patients enrolled in both the HELP and SUPPORT project with serious acute illness have a markedly different survival trajectory.

reflected by the chi-square minus the degrees of freedom for each variable.

We examined the accuracy of the model with measures of discrimination and calibration. The model had a Somers' Dxy of 0.48. The model was validated using bootstrapping. The bootstrap adjusted Dxy estimate was 0.46, indicating very good validation. The bootstrap bias-corrected calibration curve is shown in Figure 4. Perfect calibration would be indicated by a 45 degree line. For all ranges of estimates, the model prediction of survival shows adequate calibration.

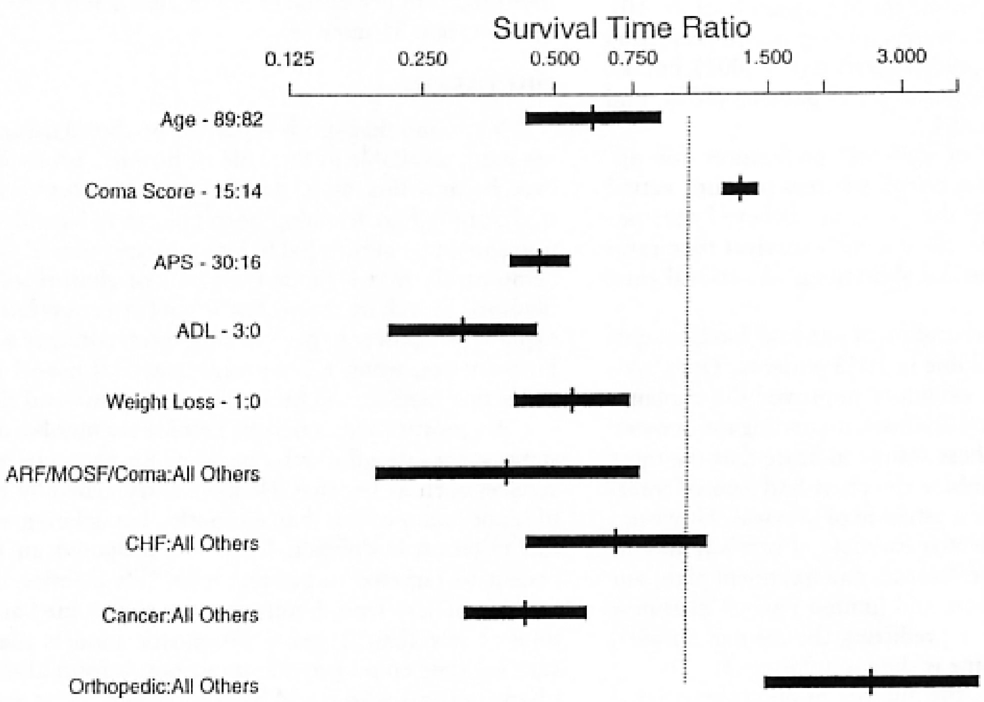

Figure 2. Survival time ratios of variables included in the final model: Estimated survival time ratios for each predictor, with 0.95 confidence limits. For continuous predictors, median survival time when the predictor is set to its 75th percentile is divided by the median survival time when the predictor equals its 25th percentile. These percentiles are rounded to the nearest whole number, and their values are listed to the right of the variable names. For weight loss, the ratio is that for patients losing weight compare with those not losing weight in the previous 2 weeks. For disease classes, all ratios have the median survival time for the "all others" category in the denominator. (APS = Acute Physiology Score of Apache 3 228 , ADL = Activities of Daily Living, ARF = Acute Respiratory Failure, MOSF = Multiple Organ System Failure, CHF = Congestive Heart Failure).

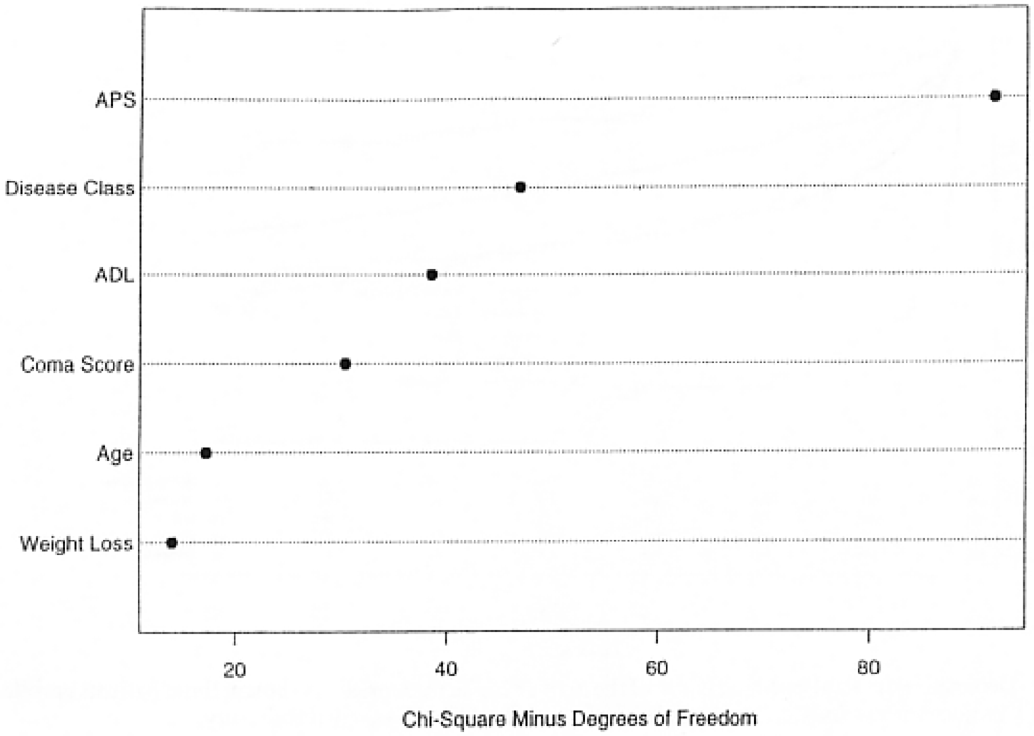

Figure 3. Importance of prognostic variables: For each predictor, the total chi-square explained by that predictor was computed. The degrees of freedom for each predictor was subtracted from the chi-square value to place the predictors on an equal footing. The chi-square minus the degrees of freedom is expect to be zero when the predictor has no association with survival time.

Effect of Additional Interview-Based Measures on Survival

Depression was not an independent predictor of mortality (P = .60). Similarly, body mass index (P = .10), vision impairment (P = .17), fall within the last 3 months (P = .10), and social support (P = .25) were not independent predictors of mortality. Albumin did predict survival (P = .001), but the value was missing in 700 cases of 1266 patients (56%) and was not included in the model.

Physician perception of patients' preferences for approach to care did predict survival, whereas patients' actual preferences did not. When the physician believed that patients wanted comfort care, the patient's survival time ratio was 0.44, indicating a marked shortening of survival time (95% CI, 0.30–0.65).

Physician subjective perception of patients' likelihood of 2-month survival was available in 1023 patients. The physician subjective prognostic estimates improved the explanatory power of the model in this subset, increasing the Somers' Dxy from 0.43 to 0.50. These results indicate that the most accurate model would combine the chart and limited interview data with the physician estimate of survival. However, because the physician subjective estimate of survival may be confounded by physician preferences and treatment plan, our final model utilizes the chart and limited patient interview data only. A nomogram for predicting the median survival time and 1-year survival time is shown in Figure 5.

To use the nomogram, the number of points associated with each listed measure should be summed. The model estimate for 1-year survival, median survival time in days, and 10th and 90th percentile of survival time may be calculated. For example, an 85-year-old patient with Other disease category, abnormal Glasgow Coma Score of 14, history of weight loss, an APS score of 30, and 1 ADL impairment would receive 25 + 0 + 7 + 43 + 18 + 16 = 109 points. One would then draw a line to intersect with the 1-year survival (62% 1-year survival rate), median survival time (about 24 months), 10th percentile (1 3/4 months), and 90th percentile (greater than 84 months).

DISCUSSION

We found that survival may be predicted using data that are easily available at the time of hospital admission. However, because this model was developed for persons hospitalized at only four teaching hospitals, an independent validation should be performed before widespread use. Our results demonstrate that a limited amount of clinical information obtained by a chart review and a brief interview has sufficient explanatory power to predict long-term mortality accurately. Furthermore, using a log-normal survival model facilitates predicting median and other quintiles of survival time.

Prognostic models may be helpful in a number of circumstances, e.g., deciding who qualifies for access to healthcare services such as hospice. Hospice entry generally requires a life expectancy of less than 6 months, but defining who meets this criterion is difficult. Lynn has proposed an insurance benefit be targeted to persons with "life defining illness."[27] Such an illness would convey an expected median survival time of less than 2 years. Prognostic models that predict survival time could provide important information by identifying persons who could be approached about enrolling in this new insurance benefit. Furthermore, both the rates of median survival and 90th percentile survival time provide important information for the patient and health insurance manager in financial planning. From the older person's perspective, estimates of median survival could provide important information about whether to take on a reverse mort-

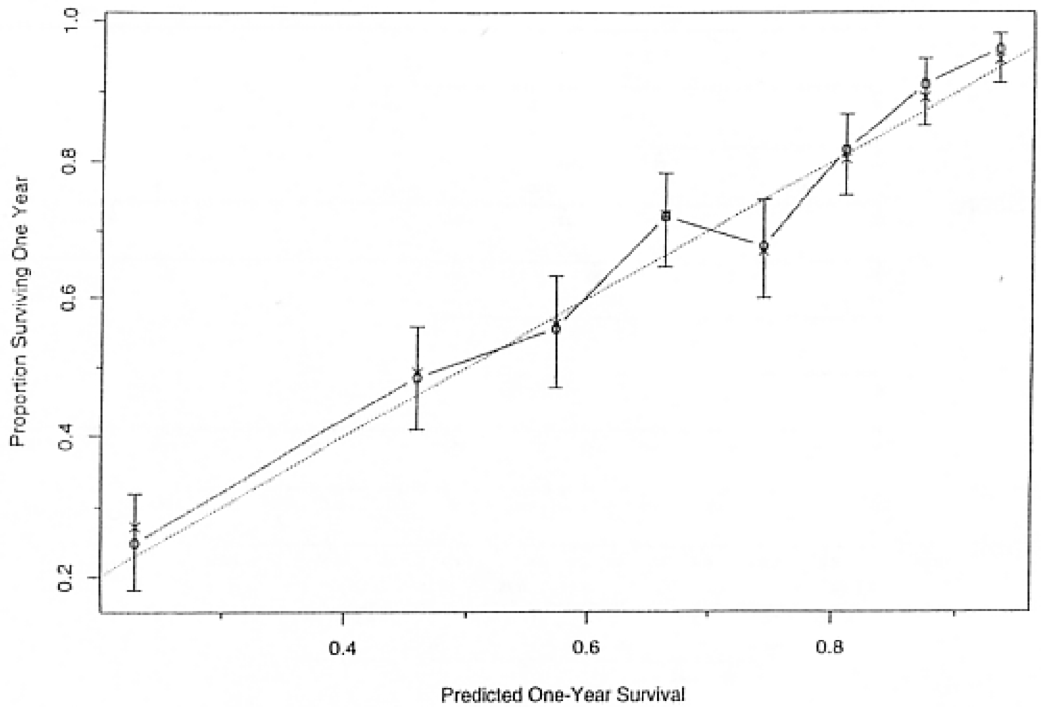

Figure 4. Calibration and bootstrap validation of the model: The data were stratified into groups containing approximately 150 patients each. For each group, the mean predicted 1-year survival probability was computed (x-axis), as was the 1-year Kaplan-Meier estimate (y-axis, depicted using circles). The 45-degree dotted line represents perfectly calibrated predictions. The difference between the circles and the 45-degree line is typically underestimated due to overfitting the data. The bootstrap was used to estimate the bias in this difference, and the bias was added to obtain overfitting-corrected estimates (shown with X) that estimate the likely accuracy of predictions on new patients. The bootstrap validation penalized for the various predictors that were tried through the course of developing the final model. This was done by including all of the candidate predictors in the model being validated, which causes an increase in the variance of predicted values.

gage or sell their life insurance policy through a viatical arrangement. The further development of prognostic models could potentially benefit both patient and healthcare providers making medical decisions.

Similar to other studies, we found that functional status[7–9,28–30] is an important predictor of long-term mortality. Our study demonstrates that these associations persist after adjustment for disease severity as measured by the APACHE III score. We found that acute disease severity was by far the strongest predictor of mortality. Age was associated with mortality, yet it was only a moderate predictor of mortality. Quite surprisingly, we found that several measures, such as depression and body mass index, were not independent predictors of survival after adjustment for disease severity and functional status. Depression has been found to predict survival time in previous studies.[8,31] However, these studies did not adjust for the patient's disease severity. Our results indicate that depression, as measured by the POMS depression subscale, was not an independent predictor of mortality after adjustment for disease severity and function. These results do not mean that depression is not associated with mortality but that the effect of depression on survival may be mediated by functional status or other physiological responses adjusted for by our disease severity measures.

History of weight loss was an independent predictor of survival time, but body mass index as measured by patient or family member self-report was not. This may reflect the limited accuracy of self-report of weight. However, we have reported that BMI as measured by self-report was associated with survival in seriously ill patients enrolled in SUPPORT.[32] We also found that similar to previous research,[33] albumin was an independent predictor of survival even after adjustment for disease severity and other factors. However, it was missing in more than one-half of the sample and we did not include it in the final model.

Of interest, we found that the physician's perception of patient preferences predicted survival time, but patient or surrogate report of patient preferences did not correlate with survival. Previously, we have reported that 6-month mortality was lower when both patient and physician preferred to forgo resuscitation.[34] These findings that only physician preferences are associated with survival raise concern. It is possible that the physician may have additional knowledge about the patient's prognosis or that physicians' perceptions of patients' preferences influence treatment in a manner that affects survival time. Further work is needed to understand this association and its causal path.

Our study has several important limitations. Our study population consisted of older persons at only four academic medical institutions and may not be generalizable to patients hospitalized at other institutions. Furthermore, our small sample did not allow us to test adequately the impact of diagnostic category in this population. Our previous work among the seriously ill suggested that diagnostic category may be an important determinant of 6-month survival time. Missing data for variables such as albumin limited our ability to include all factors in our prognostic model. The complexity of our model is increased by including the acute physiology score, yet this variable is relatively easy to calculate and should be widely available.

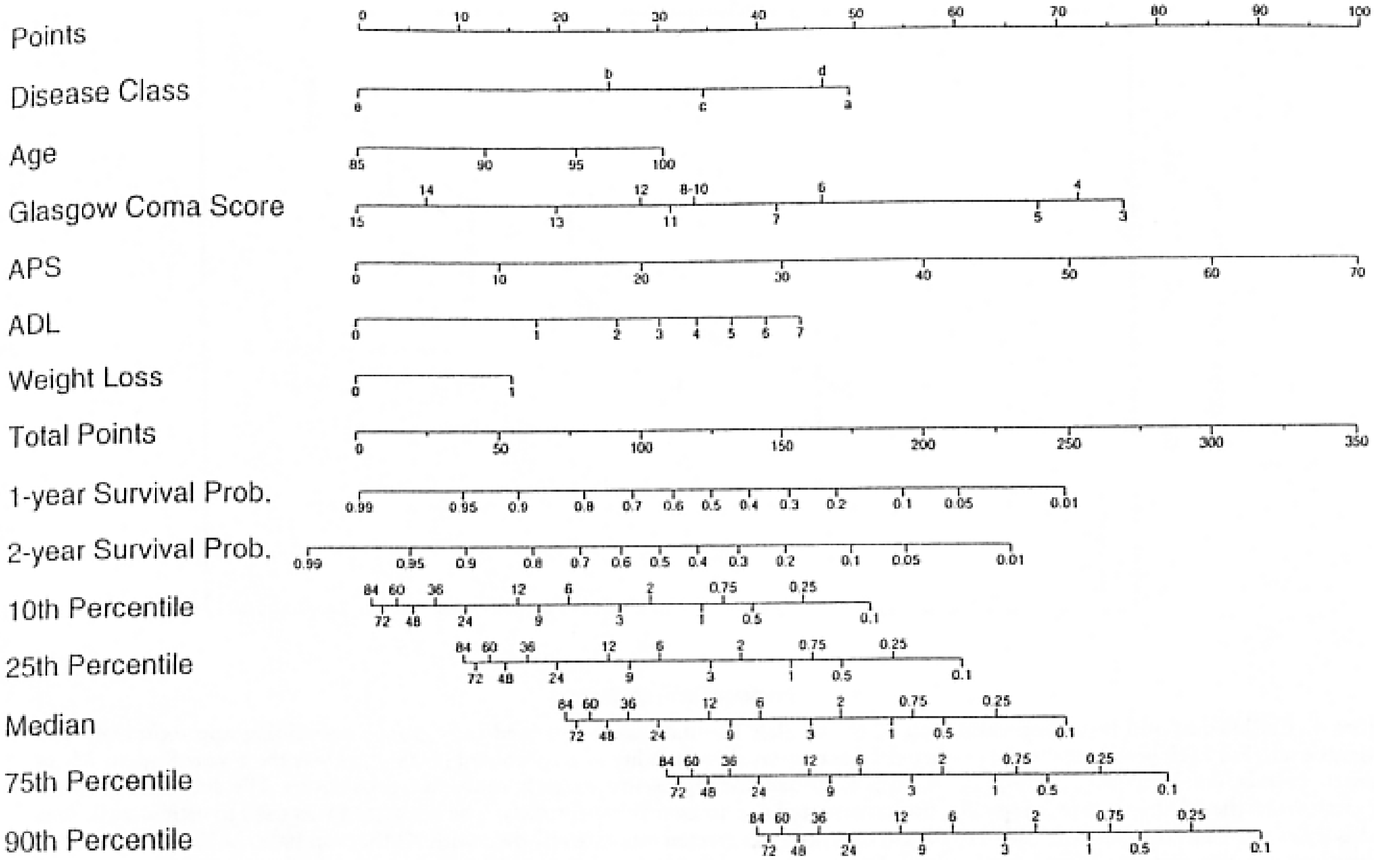

Figure 5. Nomogram for obtaining predictive 1- and 2-year survival probabilities and 10th, 25th, 50th, 75th, and 90th percentiles of survival time for individual patients. Disease classes are abbreviated as follows: a = ARF/MOSF/Coma; b = all others; c = CHF; d = Cancer; e = Orthopedic. To use the nomogram, place a ruler vertically such that it touches the appropriate value on the axis for each predictor. Read off where the ruler intersects the "Points" axis at the top of the diagram. Do this for each predictor, making a listing of the points. Add up all of these points and locate this value on the "Total Points" axis with a vertical ruler. Follow the ruler down to read off any of the predicted values of interest.

In summary, we found that a limited amount of clinical data and information from a brief interview can accurately predict long-term mortality in older hospitalized patients. These results should be validated in other hospitals before widespread use. Our finding that physician perception of patient's preferences predict long-term survival whereas patient's own preferences do not should be explored further.

REFERENCES

1. Knaus WA, Wagner DP, Draper EA et al. The APACHE III prognostic system: Risk prediction of hospital mortality for critically ill hospitalized adults. Chest 1991;100:1619–1636.
2. Pollack MM, Ruttimann UE, Getson PR. Accurate prediction of the outcome of pediatric intensive care. A new quantitative method. N Engl J Med 1987; 316:134–139.
3. Le Gall JR, Loirat P, Alperovitch A et al. A simplified acute physiology score for ICU patients. Crit Care Med 1984;12:975–977.
4. Knaus WA, Harrell FE Jr, Lynn J et al. The SUPPORT prognostic model: Objective estimates of survival for seriously ill hospitalized adults. Ann Intern Med 1995;122:191–203.
5. Hamel MB, Goldman L, Teno JM et al. Identification of comatose patients at high risk for death or severe disability. JAMA 1995;273:1842–1848.
6. Knaus WA, Draper EA, Wagner DP et al. APACHE II. A severity disease classification system. Crit Care Med 1985;13:818–829.
7. Reuben DB, Rubenstein LV, Hirsch SH, Hays RD. Value of functional status as a predictor of mortality. Am J Med 1992;93:663–669.
8. Winograd CH, Lindenberger EC, Chavez CM et al. Identifying hospitalized older patients at varying risk for physical performance decline: A new approach. J Am Geriatr Soc 1997;45:604–609.
9. Corti MC, Guralnik JM, Salive ME, Sorkin JD. Serum albumin level and physical disability as predictors of mortality in older persons. JAMA 1994; 272:1036–1042.
10. Hakim RB, Teno JM, Harrell FR et al. for the SUPPORT Investigators. Factors associated with Do-Not-Resuscitate orders: Patients' preferences, prognoses and physicians' judgments. Ann Intern Med 1996;125:284–293.
11. Hamel MB, Phillips RS, Teno JM et al. for the SUPPORT Investigators. Seriously ill hospitalized adults: Do we spend less on older patients? J Am Geriatr Soc 1996;44:1043–1048.
12. Gurwitz JH, Osganian V, Goldberg RJ et al. Diagnostic testing in acute myocardial infarction: Does patient age influence utilization patterns? The Worcester Heart Attack Study. Am J Epidemiol 1991;134:948–957.
13. Barondess JA, Kalb P, Weil WB et al. Clinical decision-making in catastrophic situations: The relevance of age. Report of a conference convened by the American Geriatrics Society, April, 17–18, 1987. J Am Geriatr Soc 1988;36:919–937.
14. Knaus WA, Douglas WP, Lynn J. Short-term mortality predictions for critically ill hospitalized adults: Science and ethics. Science 1991;254:389–394.
15. Castaneda L. Cashing in on life insurance: Healthy seniors selling policies for quick cash. The San Francisco Chronicle, Mar 31, 1998, Sect. D:1.
16. Johnston J. For the terminally ill, a path to financial peace; new options allow sick to pay bills and live rest of lives more completely. Home economics: Viatical settlements. The Boston Globe, Oct 13, 1997, Sect. A:10.
17. Winograd CH, Gerety MB, Chung M et al. Screening for frailty: Criteria and predictors of outcomes. J Am Geriatr Soc 1991;39:778–784.
18. Hlatky M, Boireu RE, Higgenbotham MB et al. A brief self-administered questionnaire to determine functional capacity (The Duke Activity Status Index). Am J Cardiol 1989;64:651–654.
19. Katz S, Ford AB, Moskowitz RW et al. Studies of the aged: The Index of ADL: A standardized measure of biological and psychosocial function. JAMA 1963;185:914–919.

20. Wu AW, Damiano AM, Lynn J et al. Predicting future functional status for seriously ill hospitalized adults: The SUPPORT prognostic model. Ann Intern Med 1995;122:342–350.
21. Cella DF, Jacobsen PB, Orav EJ et al. A brief POMS measure of distress for cancer patients. J Chronic Dis 1987;40:939–942.
22. Silliman RA. Predictors of family caregivers' physical and psychological health following hospitalization of their elders. J Am Geriatr Soc 1993;41:1039–1046.
23. Stone CJ, Koo CY. Additive Splines in Statistics. Proceedings of the Statistical Computing Section of the American Statistical Association, 1995, pp 45–48.
24. Cox DR. Regression models and life tables. J R Stat Soc 1972;34:187–220.
25. Harrell, FE, Lee, KL, Daniel, DB. Multivariable prognostic models: Issues in developing models, evaluating assumptions, adequacy, measuring, and reducing errors. Stat Med 1996;15:361–387.
26. Harrell FE. Design: S-Plus functions for biostatistical/epidemiological modeling, testing, estimation, validations, graphics, predicting and typesetting, by storing enhanced model design attributes in the fit. Unix, Linus, and Mircosoft Windows/NT versions available from lib.stat.cmu.edu. 1999.
27. Lynn J. Caring at the end of our lives (editorial comment). N Engl J Med 1996;335:201–202.
28. Mayer-Oakes SA, Oye RK, Leake B. Predictors of mortality in older patients following medical intensive care: The importance of functional status. J Am Geriatr Soc 1991;39:862–868.
29. McClellan WM, Anson C, Birkeli K, Tuttle E. Functional status and quality of life: Predictors of early mortality among patients entering treatment for end stage renal disease. J Clin Epidemiol 1991;44:83–89.
30. Rakowski W, Mor V. The association of physical activity with mortality among older adults in the longitudinal study of aging (1984–1988). J Gerontol 1992;47:M122–129.
31. Koenig HG, Shelp F, Goli V et al. Survival and health care utilization in elderly medical inpatients with major depression. J Am Geriatr Soc 1989;37:599–606.
32. Galanos AN, Pieper CF, Kussin PS et al. Relationship of body mass to subsequent mortality among seriously ill hospitalized patients. SUPPORT Investigators. The Study to understand Prognosis and Preferences for Outcome and Risks of Treatments. Crit Care Med 1997;25:1962–1968.
33. McMurty CT, Rosenthal A. Predictors of 2-year mortality among older male veterans on a geriatric rehabilitation unit. J Am Geriatr Soc 1995;43:1123–1126.
34. Teno JM, Hakim RB, Knaus WA et al. for the SUPPORT Investigators. Preferences for CPR: Physician-patient agreement and hospital resources. J Gen Intern Med 1995;10:179–186.